Measuring Complexity and Reproducibility

A Comprehensive Benchmark of LLMs for Multilingual Policy Agenda Topic Annotation

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Introduction

Research Overview

Benchmark study. Testing 79 contemporary LLMs on zero-shot classification of policy topics.

Multilingual approach. Covering Danish, Dutch, English, French, Hungarian, Italian, Portuguese and Spanish.

Performance analysis. Evaluating how reasoning capabilities, model architecture and deployment affect accuracy.

Artwork by Leonardo Phoenix model

The Challenge of Policy Annotation

Artwork by DALL·E 3 model

⚖ **Complex classification.** Assigning one of 21 major policy topics to legislative texts.

Language barriers. Working across eight different languages with varying resources.

Semantic nuance. Requiring fine distinctions between related policy areas.

Reproducibility concerns. Balancing performance with scientific reproducibility.

Empirical Expectations

Research Hypotheses

Reasoning Advantage Hypothesis

LLMs explicitly optimised for chain-of-thought (CoT) reasoning will achieve better performance in zero-shot policy agenda classification.

Openness Penalty Hypothesis

Proprietary, closed-source LLMs will outperform open-source LLMs on zero-shot policy agenda classification.

Reproducibility Penalty Hypothesis

LLMs deployed locally using a deterministic sampling will achieve lower performance in zero-shot policy agenda classification.

Methods

Ground-Truth Data

Denmark	NLD	UK	France
15 101 bills 1953–2016	4 684 bills 1981–2009	6 169 Acts 1911–2015	3 069 laws 1979–2013

Hungary	Italy	Brazil	Spain
8 220 bills 1990–2022	4 554 laws 1983–2013	2 449 laws 2003–2014	2 256 laws-decrees 1980–2018

Note. We split the samples in a proportion of 70/15/15 (stratified by major topic) for training, validation, and testing for future fine-tuning jobs. The samples correspond to ground-truth data of the Comparative Agendas Project.

LLMs Zero-Shot Classification

79 LLMs

Run **620 times** under different conditions (e.g., parameters, API/local, temperature, datasets/language) for

(1) **overall performance metrics**
(2) **meta-analysis**

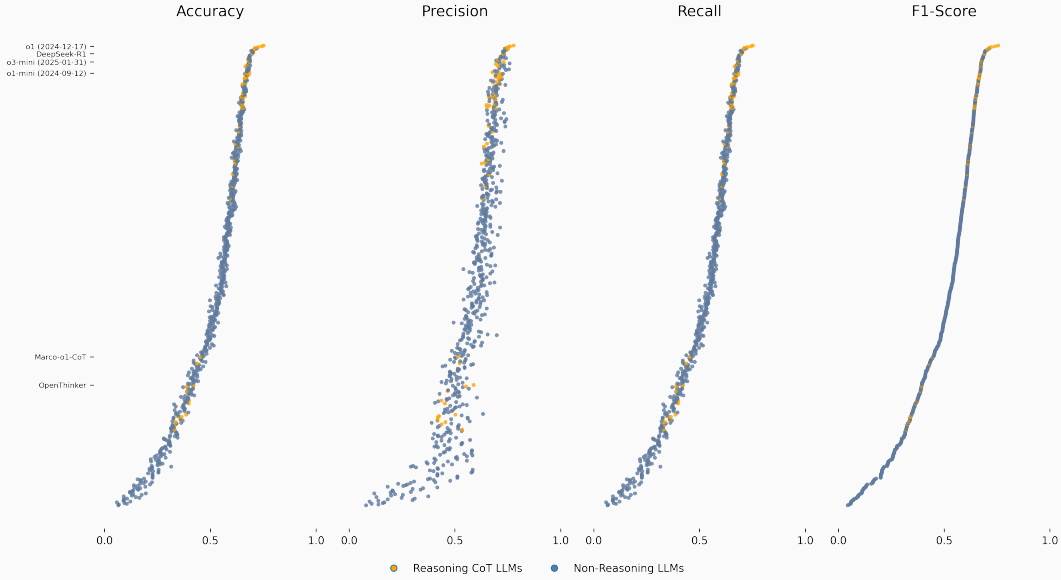
SOTA closed-source LLMs

o4-mini, o3-mini, o1, GPT-4.1, GPT-4.5-preview, Grok 3 Beta, Claude 3.7 Sonnet, among others

SOTA open-source LLMs

Llama 4 Maverick (400B) and Scout (107B), Mistral 3.1 (24B), Llama 3.3 (70B), DeepSeek-R1 (671B), DeepSeek-V3 (671B), among others

Results


Accuracy
Precision
Recall
F1-Score
o1 (2024-12-17)
DeepSeek-R1
o3-mini (2025-01-31)
o1-mini (2024-09-12)
Marco-o1-CoT
OpenThinker
0.0
0.5
1.0
Reasoning CoT LLMs
Non-Reasoning LLMs

Top Performing Models

0.76

Maximum F1-Score

Achieved by OpenAI reasoning models

0.69

Top Open-Source Models

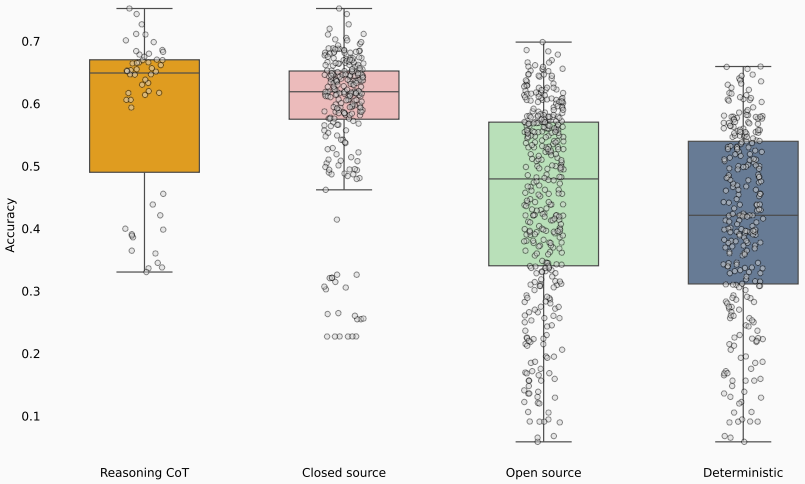
DeepSeek-R1 and V3 (926B) and Llama 3.1 (405B)

0.54

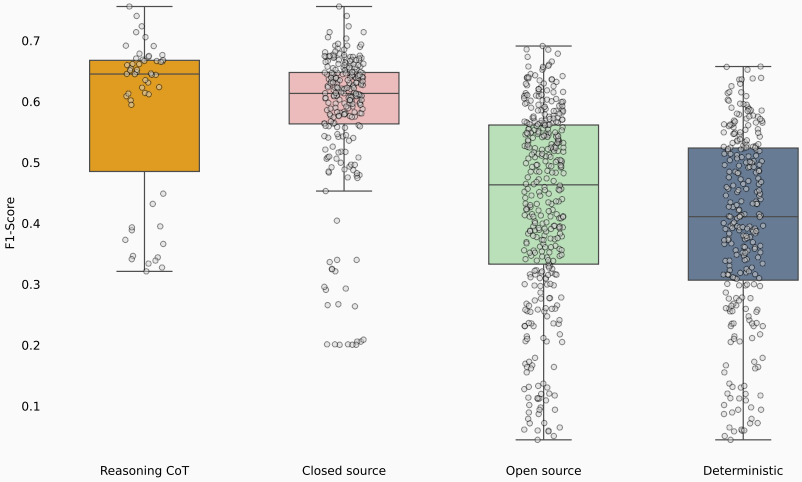
Mid-Range Performance

Gemini 1.5 series, GPT4o-mini, Mistral models, Qwen 2.5

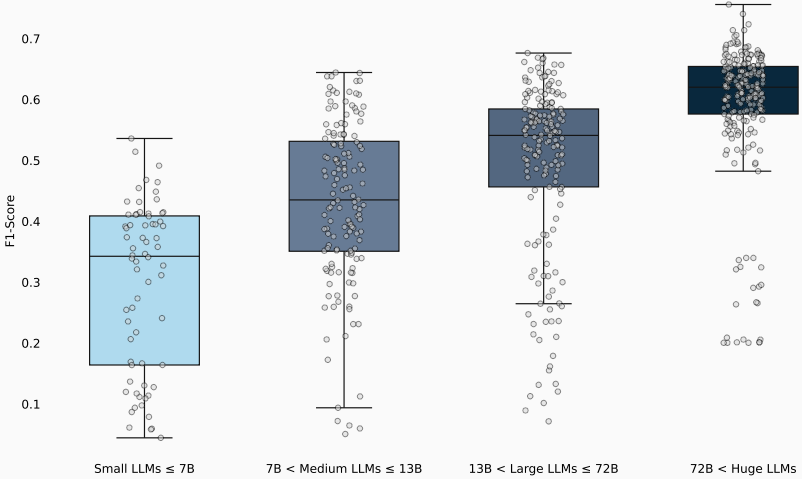
Accuracy Across Reasoning, Source and Deterministic Setup



F1-Score Across Reasoning, Source and Deterministic Setup



F1-Score Across Number of Parameters



Determinants of Performance

	Model I	Model II	Model III	Model IV	Model V
Reasoning CoT	0.462***	0.323***	0.296***	0.359***	0.357***
	(0.031)	(0.096)	(0.092)	(0.086)	(0.086)
Open source LLMs		−0.637***	−0.205***	−0.128*	−0.126*
		(0.056)	(0.076)	(0.072)	(0.071)
Deterministic setup			−0.591***	−0.328***	−0.330***
			(0.075)	(0.076)	(0.075)
Constant	−0.112***	0.287***	0.291***	−0.476***	−0.285**
	(0.105)	(0.045)	(0.043)	(0.092)	(0.112)
Parameters	No	No	No	Yes	Yes
Language FE	No	No	No	No	Yes
N	620	620	620	620	620
τ	0.734	0.665	0.633	0.592	0.590
I^2	99.04%	98.84%	98.72%	98.54%	98.53%
R^2	0.029	0.203	0.277	0.368	0.372

Next Steps

Comparing with Fine-Tuned Models

Language	Best LLM	F1-Score	Fine-Tuned	F1-Score	Δ Val	Δ Best LLM
Danish	GPT-4.5	0.679	Babel Machine	0.925	+0.065	+0.246
Dutch	o1	0.724	Babel Machine	0.906	+0.066	+0.182
English	o1	0.706	Babel Machine	0.869	−0.031	+0.163
			ft-XLM-RoBERTa	0.810	−0.009	+0.104
French	o1	0.714	Babel Machine	0.821	−0.029	+0.107
Hungarian	GPT.4-5	0.672	Babel Machine	0.751	−0.099	+0.079
Italian	o1	0.675	Babel Machine	0.930	+0.120	+0.255
Portuguese	o1	0.651	Babel Machine	0.867	−0.063	+0.216
Spanish	o4-mini	0.756	Babel Machine	0.916	+0.066	+0.160

Note. All estimates are weighted F1-scores obtained on our fixed held-out test set. The columns Δ Val and Δ Best LLM indicate: (i) the change relative to the best result on the model's own validation set; and (ii) the change relative to the strongest zero-shot LLM, respectively.

How much data leakage is present here? Probably considerable, so that the results may be inflated. However, the potential advantages of fine-tuning still seem to outweigh in-context learning, even for BERT-like models.

Focus on Specific Topics: Environment and Energy

AI-Driven Text Analysis in the Political Economy of Sustainability: Hybrid Retrieval-Augmented Generation and LLM Multi-Agent Approach (ECPR Joint Sessions):

LLM	Accuracy	Precision	Recall	F1-Score
o3	0.968	0.906	0.993	0.948
Hermes 3 (70B)	0.965	0.927	0.956	0.941
GPT-4o	0.964	0.910	0.973	0.940
Grok 3 Mini Beta	0.964	0.913	0.969	0.940
GPT-4.5-preview	0.963	0.895	0.990	0.940
Nemotron (70B)	0.963	0.907	0.973	0.939
Grok 3 Mini Fast Beta	0.963	0.913	0.966	0.938
GPT-4.1	0.962	0.894	0.986	0.938
Grok Beta	0.962	0.894	0.986	0.938
GPT-4.1 mini	0.962	0.897	0.983	0.938

Takeaways

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$+8.9\%$

Reasoning Advantage

Chain-of-thought capabilities boost F1-score by almost 9 points

-7.8%

Reproducibility Penalty

Deterministic deployment reduces F1-score by about 8 points, but ensures consistency

$\geq 10\%$

Fine-Tuning Advantage

Supervised transformers outperform zero-shot LLMs by 10+ points

We did not find 🔒 openness penalty

Thank you very much!

Do you have any questions?

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Presentation compiled with LaTeX and some

Download the latest version from GitHub